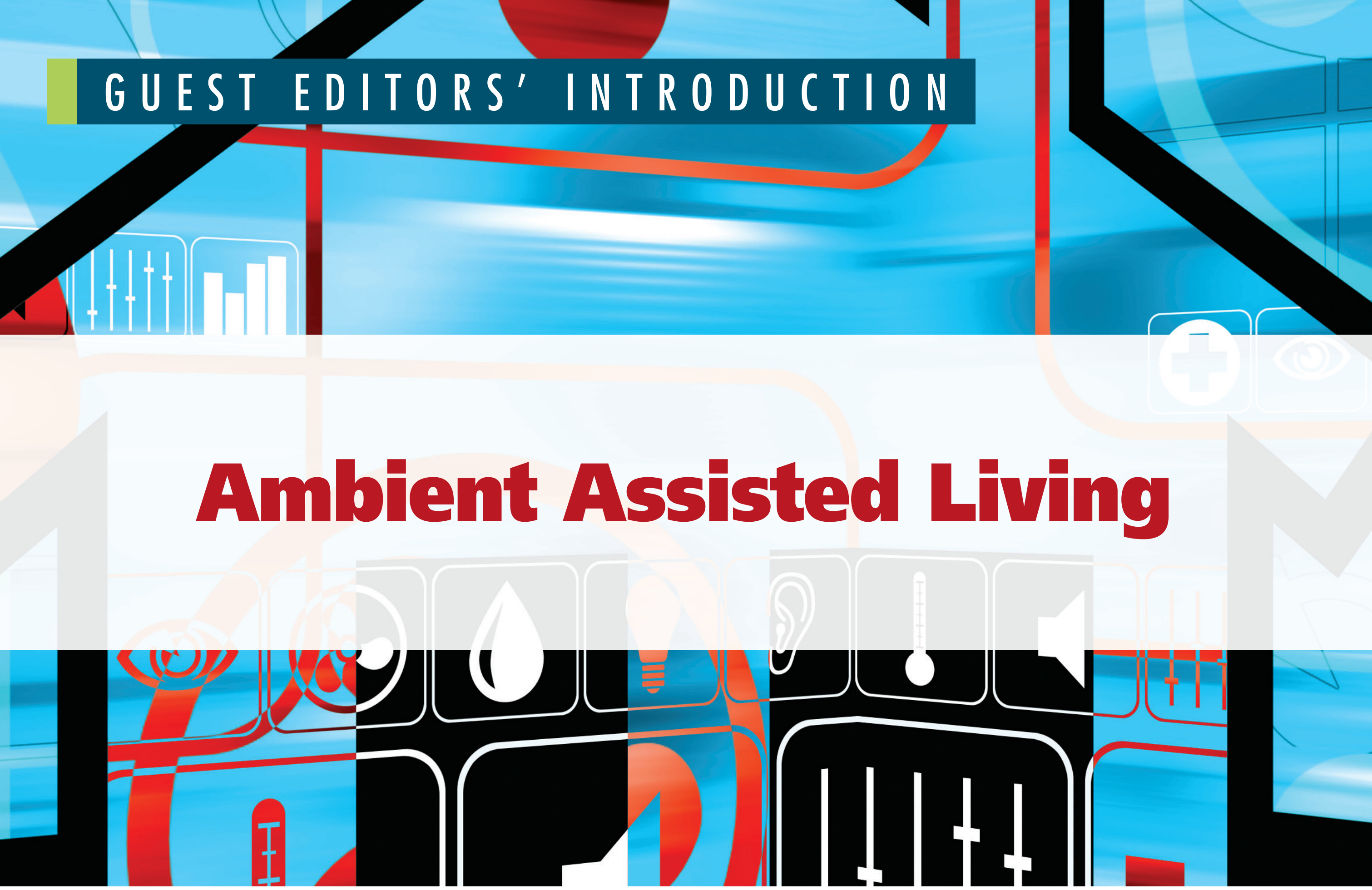
GUEST EDITORS' INTRODUCTION



Ambient Assisted Living

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The world population is aging rapidly. According to the UN's Economic and Social Affairs (EC-ESA), Population Division, by 2050, the number of older people (over 65 years of age) will exceed the younger population for the first time in history (www.un.org/en/development/desa/population/theme/ageing/index.shtml).

The old-age dependency ratio—that is, the ratio of older dependents (people older than 64) to the working-age population (those aged 15 to 64)—is rising, particularly in the more developed nations. The impact of this demographic change is widely recognized, as is the need to address the problem both from a societal and an economic standpoint. Research into aging, age-related conditions, and the means to support an aging population has therefore become a priority for many governments around the world.

Ambient assisted living (AAL) can be defined as "the use of information and communication technologies (ICT) in a person's daily living and working environment to enable them to stay active longer, remain socially connected and live independently into old age" (www.aal-europe.eu). Research in the AAL community covers a wide range of topics, but one of the largest is human activity recognition and behavior understanding, with the objectives of detecting and recognizing actions, activity, and situations within an environment.

Event detection is an important topic in the AAL community, particularly fall detection. The most commonly used sensors for

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Published by the IEEE Computer Society

detecting falls are wrist or waist worn, but these have many limitations, not least being that the device must be worn at all times. More recently, researchers have turned to vision-based fall detection, which has its own challenges, including clutter, occlusions, and so on. Complicating the situation is the fact that statistics show most falls occur in the bathroom—a location where privacy concerns are highest. To address this issue, researchers are investigating privacy-aware techniques that hide detail from video streams either computationally or with the use of IR sensing.[1]

AAL systems go beyond observing to interact with users. A frequently employed form of human-machine interaction is via prompts—for example, prompting the user to perform the next step in a sequence of actions.[2–4] Another type of interaction is haptic responses, which have been used in systems for visually impaired people.[5] Two important elements of an appropriate response are an understanding of the user's context and anticipatory capability. *Context awareness* underpins much of AAL research—human activities are generally context dependent. In the broader sense, context awareness uses sensor observations to abstract information about the current situation.[6] Endowing a system with *predictive capability* lets it anticipate and thereby produce a timely and useful response.

A Brief Introduction to AAL Research

AAL can trace its roots back to home automation and assistive domotics. In recent years, work in the field has intensified, taking advantage of new developments in sensor technology, reduced sizes and costs, and increased processing power in computing devices. The AAL research community borrows from a more mature field of research—video surveillance. But unlike video surveillance, which employs a single sensor modality, AAL uses a variety of sensors for activity recognition and behavior understanding,[7] sensing directly via wearable sensors or indirectly through environmental sensors and analyzing the streaming data to infer something about the physical or cognitive status of the person observed.[8]

Research into activity recognition and behavior understanding covers a broad range of methods and techniques dependent on the type of

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sensors employed and the required detail. Activity recognition uses very simple, unobtrusive sensors to reduce privacy concerns and increase acceptance. Most sensors in this category measure environmental parameters, deducing human activity from observation. Such sensors include motion, pressure pad, temperature, lighting, appliance status, door contact, and so on.[9–13] Simple sensors provide very coarse information—for example, a motion detector would indicate that a person is in the kitchen, and door contacts will indicate activity

IEEE Intelligent Systems

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around cupboards, but little additional information about actual activity can be extracted; instead, it's inferred. Video technology is increasingly used because it can provide a great deal more information, albeit at a much higher computational cost. The use of video for activity recognition has received much attention in recent years.[14–16]

Wearable sensors are another class employed in activity recognition. Inertial measurement units (IMUs) are the most frequently encountered,[17–19] and because most smartphones incorporate them, they have been opportunistically used for activity recognition, although the recognition is normally restricted to differentiating sitting, walking, and running activities.[20–23] Other classes of wearable sensors are physiological and biochemical.[24,25]

It's often necessary to locate an object or a person. The precision of the required localization varies from coarse (room level) to a more precision location within a room. Coarse location is provided by sensors that track motion (for single or low occupancy environments) or via radio-based technology,[26] the use of which has received increased attention because of the opportunistic use of existing wireless network infrastructure and smartphones.[27–29] More precise indoor localization and tracking can be achieved by using radio signal strength for trilateration—other options include IR sensors placed in a dense grid to locate the person or moving object within grid cells.[30]

Human-human or human-object interaction has been investigated for the purpose of understanding ongoing activity[31] or for performance and clinical assessment.[32–37]

In This Issue

The topics of interest for this special issue include applications of AAL (technologies, tools, and systems) to support health, well-being, social inclusion, robotics, intelligent sensors, smart spaces, and digital assistants with relevant computational methods and techniques.

This special issue contains five contributions, two of which ("Exploiting Passive RFID Technology for Activity Recognition in Smart Homes," by Dany Fortin-Simard and colleagues, and "Using RFID to Detect Interactions in Ambient Assisted Living Environments," by Raúl Parada and colleagues) describe the use of RFID technology for activity recognition. RFID has long been used for assessment management and tracking. In both articles, human-object interactions are detected via RFID. The Fortin-Simard team justifies the use of RFID as a means to counter privacy concerns through a Gaussian mean weighting filter, the Parada team fuses data from a light sensor prior to using a weighted Information Gain classifier. The additional sensor provides additional evidence to confirm or dispel the presence of objects.

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The remaining articles describe the outcome of designing and designing whole systems. In "FridgeNet: A Nutrition and Social Activity Promotion Platform for Aging Populations," Yuju Lee and colleagues introduce a system for diet monitoring and food recommendation. The objective is to promote healthy diets in older people. The system facilitates communication between different users to compare their food intake, recommend meals for a balanced diet, and send invitations to other users to purchase food together. As such, FridgeNet provides a mechanism to counteract social isolation while promoting an active and healthy aging.

In "Bridge: Mutual Reassurance for Autonomous and Independent Living," Simone Mangano and colleagues propose an architecture to assist the caring of elderly people. The project was conceived from the ground up based on real user requirements. The system has an intelligent management system that allows some degree of reasoning about an unfolding series of events. The remote module is implemented for the remote carer, with remote access adhering to a privacy agreement between the cared-for person and the carers. The article reports on case studies, including vocal command for home automation, unobtrusive presence detection, and event notification via Twitter.

The third article in this category describes the SPHERE project—in "Bridging e-Health and the Internet of Things: The SPHERE Project," Ni Zhu and colleagues introduce a solution to provide AAL services at home. Such solutions require addressing several issues, including sensor data acquisition, ontologies definition, interoperability, data ownership, privacy, acceptability, and context awareness. This article presents an overview and outlines the approach considered in SPHERE to address these issues.

Activity recognition and behavior analysis have received much attention, and the research community is growing fast. Significant advances have been made, but much remains to be done, especially to improve system robustness and to create reliable applications that will work successfully in the field. Much of the work employs statistical techniques and therefore requires plenty of training data. Given the nature of the application, "real" data might be difficult to come by—for example, monitoring a person at home with tens of sensors generates lots of data daily even though relatively little activity is observed. The AAL research community is setting up repositories of smart home data that can be used by all researchers. Another issue is that the typical actions, activities, and situations that one is looking to observe are difficult to reproduce faithfully in laboratories, and it's even more difficult (for reasons of ethics, privacy, and logistics) for engineers and computer scientists to set up experiments to collect such data in real homes.

Early research in the field rarely involved the user in the process. This was in part because AAL in some respects was borne out of intelligent home automation, but more importantly, because researchers generally found it difficult to come by data (specifically the large amounts of data needed to develop learning systems). Today, more users are involved with data collected in their homes, and cross-disciplinary projects explicitly seek out users to help social scientists and healthcare professionals. This is an exciting time to be working in this field! ■

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